Classification of Counterfeit Brake Shoe using Machine Learning

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"I write my dissertation as a tribute to my dear family."

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Table of Contents

Abstract

This thesis probes how Machine Learning (ML) can be used to distinguish between original and counterfeit brake shoe. The research uses a dataset of images collected from different cities (Islamabad, Lahore, Faisalabad, Rawalpindi and Multan). There are two types of brake shoe images in the dataset: original and counterfeit; the data is labelled into these two classes accordingly and fed to the ML models used. Three specific machine learning models, Constitutional Neural Network (CNN), Multi-layer Perceptron (MLP) and VGG 19 are applied for distinguishing genuine and fake products. By using a dataset that represents a vast variety of brake shoes in local markets, the models are made more robust and adaptable. Moreover, the research methodology involves an examination of the architecture, training process and evaluation metrics of each model. Confusion matrices are used to evaluate how well the models can differentiate between fake and original brake shoe. Additionally, accuracy measures such as precision, recall and F1 score are calculated to offer an assessment of model performance. Furthermore, a comparative analysis is carried out to determine which model is most effective at distinguishing two classes of brake shoes. The findings show that the VGG 19 model surpasses the CNN and MLP models in terms of accuracy and reliability in classification tasks. VGG19 showed an accuracy of 0.92 compared to 0.90 and 0.81 of CNN and MLP respectively. For precision as well VGG19 outnumbered other models with score 0f 0.93 in comparison to 0.84 and 0.90 of MLP and CNN respectively. Similarly recall and F-1 score of VGG19 was higher than other two models used. These results affirmed the usage of VGG19 for usage in future works. These approaches help in distinguishing between real and fake brake shoes, which in turn is very effective towards anti-counterfeiting. In general, this study sheds light on how machine learning can be applied to combat counterfeit products specifically focusing on brake shoes. The results offer insights for industry players, policymakers and researchers working on counterfeiting initiatives highlighting the significance of utilizing advanced technologies to tackle this global issue.

CHAPTER 1

Introduction

1.1 A Historical Overview of Counterfeit Products

Fake goods, which negatively affect economies, industries and consumer well being have a long past that goes back thousands of years ; The roots of this illegal activity can be linked to ancient societies [1].

Counterfeit products have a connection, to barter systems, where people sometimes tried to trick others by presenting fake goods instead of authentic ones. As time passed these deceptive tactics progressed alongside improvements and shifts, in trading paths.

In Rome there are records of the known incidents of counterfeiting involving the production of fake coins to disrupt the economy. The Roman authorities implemented measures to tackle this practice, such, as issuing official statements and imposing harsh punishments on those involved in counterfeiting. [2].

Throughout the advancement of societies, the techniques and objectives of counterfeiting also evolved. For example during the revolution of the century there was a notable increase, in fake goods due, to the widespread adoption of mass production. This era signaled the start of a struggle for authorities and businesses to safeguard consumers and lawful enterprises.

During the 20th century counterfeiting evolved significantly due, to the expansion of trade. The manufacturing and selling of goods turned into a coordinated criminal operation with networks operating across various countries. Counterfeit products encompassed a range of items from high end fashion accessories to items such as medicines and even spread into crucial safety related industries, like automotive parts.

In this era the issue of goods has grown significantly. The rise of platforms and e commerce has provided counterfeiters with access, to global markets. This situation has sparked worries not about consequences but also about the potential dangers associated with counterfeit products particularly in sectors such, as automotive, where inferior components can result in severe accidents.[3].

During this age of progress, the fields of machine learning and artificial intelligence present valuable resources in the fight, against the increasing challenge posed by fake goods. This study explores how machine learning methods can be utilized to identify brake shoes playing a role, in the effort to tackle this widespread issue.

Counterfeit products come in a wide range of types and can extend to virtually any product or industry. Here are some common types of counterfeit products:

- **Counterfeit Currency:** Fake banknotes and coins created with the intent to deceive and circulate as genuine currency.
- **Counterfeit Luxury Goods:** Knockoff or imitation versions of high-end luxury brands, including clothing, handbags, watches, and accessories.
- **Counterfeit Pharmaceuticals:** Fake medications that mimic legitimate drugs but often lack proper ingredients or quality control, posing serious health risks to consumers.
- **Counterfeit Electronics:** Imitation electronic devices such as smartphones, tablets,and chargers that are often substandard in terms of performance and safety.
- **Counterfeit Automotive Parts:** Fake or substandard vehicle components, including brake pads, airbags, and engine parts, which can compromise vehicle safety.
- **Counterfeit Software and Media**: Illegally copied or replicated software, movies, music, and video games.
- **Counterfeit Cosmetics and Personal Care Products:** Imitation beauty and personal care items that may contain harmful ingredients.
- The creation and circulation of goods present substantial economic, health and safety hazards. Strategies to address counterfeiting include actions, educating consumers and utilizing technologies, like authentication methods and machine learning to identify and stop the proliferation of items.

1.2 Understanding Counterfeiting in the Automotive Industry

The automotive sector, a part of transportation and commerce has seen significant growth and advancements over the years. However, it has also faced challenges, one of the notable being the infiltration of car parts, into its supply chain. This section aims to explore the issue of counterfeiting in the industry discussing its origins, consequences and its impact on road safety and economic stability.

Origin of Counterfeiting:

Counterfeiting in the industry can be traced back to its expansion in the 20th century. With increasing vehicle production to meet demands came opportunities for dishonest individuals to produce and distribute parts. Initially these counterfeit products were imitations targeting essential components.. As the industry progressed so did the sophistication of counterfeiters.

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Economic Impacts*:*

Counterfeit car parts present risks. Legitimate manufacturers and distributors often suffer from revenue losses due to competition from products. Moreover, consumers who unknowingly buy these parts may face setbacks as they are prone to early failure and can lead to costly vehicle damage requiring repairs.

Safety Concerns:

One of the worries related to fake automotive components revolves around safety. Brake shoes serve as an example of the risks associated with parts. The use of materials and manufacturing methods, in brake shoes can result in decreased braking effectiveness longer stopping distances and an increased likelihood of accidents. In situations where brake shoes fail drastically it can lead to accidents causing injuries or even fatalities.

Global Supply Chain Complexity:

The automotive industry functions within an intricate global supply chain making it difficult to oversee and regulate the movement of parts. Counterfeit components can infiltrate this chain at stages from production to distribution making identification and prevention a challenge.

Regulatory Responses:

Governments and industrial organizations worldwide have acknowledged the necessity to combat parts. They have put into place a variety of regulations and standards designed to tackle counterfeiting and ensure the safety and dependability of elements. These initiatives encompass quality checks, labeling prerequisites, and penalties for those involved in counterfeiting activities.

1.3 Machine Learning in Counterfeit Detection

The issue of products has spread worldwide affecting industries and posing risks to both consumers and genuine businesses. In the fight, against goods, artificial intelligence (AI) and machine learning have become tools offering advanced capabilities in detecting categorizing and preventing such activities. This article delves into the role of AI, machine learning in detecting counterfeits highlighting the methods, obstacles and far-reaching consequences of leveraging these technologies to ensure authenticity and safeguard consumers.

- **Data-Driven Counterfeit Detection:**

AI powered counterfeit detection relies on data driven decision making. Through machine learning algorithms analyzing datasets containing information on fake products they can identify complex patterns and distinctive features that may escape human scrutiny. This data centric strategy proves invaluable when dealing with variations used by counterfeiters to replicate items.

- **Feature Extraction and Analysis:**

A key aspect of utilizing machine learning for counterfeit detection involves extracting and analyzing relevant features, from products. These features encompass a range including attributes, packaging details, materials utilized and even intricate design elements.
When dealing with car parts, like brake shoes the key features to consider are the materials used in the brake pads, surface textures sizes and how they are made. It's crucial to pick out features for machine learning models to work effectively.

- **Supervised Learning Models:**

In detecting counterfeits supervised learning methods play a role. These models get trained on datasets with labeled examples of fake products. By learning from these examples the algorithms become skilled at telling them and acting as detectors. When new samples without labels come in these models can predict their authenticity.

- **Interpretability and Explainability:**

In industries where safety's critical like automotive and healthcare understanding how machine learning models make decisions is crucial. Knowing why a model identifies a product as real or fake is necessary for validation and decision making processes. Techniques such, as analyzing feature importance and using model frameworks help provide this insight ensuring that decisions based on AI detection are transparent and reliable.

- **Scalability and Automation:**

Machine learning enhances scalability and automation in detecting counterfeits. After being trained, these models can efficiently handle a number of products in a speedy manner decreasing the need, for manual checks and lowering the chances of human mistakes. This ability to scale is especially beneficial, in manufacturing and distribution setups, where relying on manual inspections might not be feasible.

1.4 Counterfeit Automotive Parts in Pakistan

The issue of counterfeit car parts has become a very serious issue in Pakistan's automotive sector. This section delves into the difficulties posed by auto components highlighting their widespread presence, effects and the urgent need for creative solutions in this field.

Prevalence and Scope: Counterfeit car parts, such as brake shoes, have spread extensively in Pakistan's market of automobiles. These imitated parts often look very similar to original ones making it challenging for consumers and even experts to distinguish between them. The prevalence of auto parts poses risks to both road safety and the overall integrity of the automotive market

Impact on Road Safety: Counterfeit automotive parts, especially those related to safety systems like brakes raise serious concerns regarding road safety. For instance, using materials and manufacturing methods in brake shoes can result in reduced braking effectiveness longer stopping distances and an increased risk of accidents. The outcomes of brake failure caused by parts can be disastrous leading to injuries and loss of life.

Economic Implications: The infiltration of counterfeit automotive parts have serious economic repercussions. Legitimate companies and sellers, in the automotive sector experience a decrease in earnings sue to counterfeit competition. Moreover, buyers who unintentionally buy counterfeit parts may encounter setbacks since these items are likely to fail early and could lead to significant vehicle damage requiring expensive fixes.

Intellectual Property Rights and Regulatory Response: Securing intellectual property rights plays a role in tackling counterfeiting. Pakistan has made efforts to address this issue by introducing intellectual property laws and regulations. Both the government and industry have put in place strategies to reduce the production of parts, such, as enforcing higher quality standards and imposing penalties on those involved in counterfeiting.

1.5 Advantages of Utilizing Machine Learning forDetecting Counterfeit Automotive Parts in Pakistan

The application of machine learning techniques to detect counterfeit automotive parts in Pakistan represents a pivotal step forward in addressing the multifaceted challenges posed by counterfeit components within the automotive industry. This page outlines the significant advantages and transformative potential of leveraging machine learning in this critical domain. The application of Machine Learning technique to recognize counterfeit parts is a very important step to counter challenges posed by counterfeiting in the automotive industry of Pakistan. This section highlights the benefits and transformative opportunities of using machine learning in this field.

- **Enhanced Accuracy and Precision:**

When machine learning models are taught using sets of data that include fake components, they become adept at spotting subtle nuances and unique characteristics that might be missed by human inspectors. This improved ability to detect with precision greatly lowers the chances of identifications making sure that fake parts are pinpointed reliably.

- **Early Detection:**

In the phases of the supply chain machine learning algorithms can quickly spot parts. Detecting counterfeits is vital to stop them from reaching customers and vehicles which helps reduce safety risks and financial damages.

- **Scalability:**

As Pakistan's auto industry grows, the importance of ways to detect counterfeit parts becomes more apparent. Machine learning algorithms are scalable, and they are capable enough to handle a number of parts consistently which is crucial for big automotive production and distribution networks where relying solely on manual inspection may not be feasible

- **Efficiency:**

Automating the identification of products using machine learning greatly improves how efficiently operations run. This technology allows manufacturers and regulatory agencies to swiftly evaluate quantities of components minimizing the reliance, on labor manual checks. The resulting increase, in efficiency leads to cost reductions and a smoother flow of supply chain activities.

- **Continuous Improvement:**

Machine learning systems possess the ability to learn and adjust over time. When new information is introduced and counterfeiters change their strategies these systems can be. Trained again to keep up with the threats. This flexible approach helps ensure that counterfeit detection remains efficient, in dealing with changing obstacles.

- **Reduced Human Error:**

Human inspectors can make mistakes. Get tired affecting how well they spot counterfeits. Machine learning helps by offering impartial and tireless examination of components thus lowering the chances of mistakes.

- **Data-Driven Insights:**

Machine Learning yields insights based on data. These insights help in detecting patterns of activities and recognizing shared characteristics, among products. By leveraging these findings, specific actions and regulations can be implemented to combat counterfeiting.

- **Resource Optimization:**

Machine learning can enhance the allocation of resources, for inspection and authentication tasks. By prioritizing areas, with a likelihood of containing items as predicted by machine learning resources can be used effectively increasing the effectiveness of detection efforts.

1.6 Problem Statement

The automotive industry in Pakistan is facing some serious issues of counterfeiting especially counterfeit brake shoe. The manual inspection and identification of brake shoes demand resources and are prone to errors. As a result, there is a pressing requirement for an effective automated system to accurately categorize brake shoes. This study aims to tackle this challenge by harnessing the potential of machine learning to create a classification model that can swiftly and precisely detect counterfeit brake shoes, within the Pakistani automotive industry.

1.7 Aims

- Develop a robust machine learning model for accurate counterfeit brake shoe classification.
- Enhance consumer safety by preventing counterfeit brake shoes from entering the automotive supply chain.
- Reduce economic losses incurred by manufacturers, distributors, and consumers due to counterfeit automotive parts.
- Inform regulatory measures and policies to curb counterfeiting within the automotive industry in Pakistan.

1.8 Objectives

- **Develop a Machine Learning Model:** Design a machine learning system that can effectively differentiate between authentic and fake brake pad
- **Collect and Prepare Data:** Collect information, about brake shoe attributes

such as the type of materials used, sizes, outer appearance and how they are made.. Refine the data before training and assessing the model, clean the data for model training and evaluation.

- **Enhance Detection Accuracy:** Consistently enhance the machine learning algorithm to boost its precision, in detecting brake pads reducing instances of positives and negatives.

- **Evaluate Real-World Applicability:** Regularly adjust the machine learning algorithm to improve its accuracy, in identifying brake pads thereby reducing errors in both detection and identification.

- **Contribute to Road Safety:** Let's work towards improving road safety in Pakistan by stopping the use of brake shoes, in vehicles. This way we can lower the chances of accidents and injuries resulting from brake malfunctions.

1.9 Thesis Organization

In the quest to address the issue of brake shoes in the Pakistani automotive sector, this thesis is divided into five chapters each offering a unique perspective on the investigation. The first chapter lays the groundwork by explaining the background outlining our goals defining our study objectives and setting up a flow to guide readers through our research journey. Moving on to Chapter 2, we broaden our view by presenting a concise summary of previous research in this area. This chapter not only recognizes advancements made in studies but also identifies gaps that highlight the importance of our research. Chapter 3 delves into our research methodology uncovering the processes involved in data collection classification methods used, explanations of algorithms employed and a thorough analysis of changes spanning two decades. Transitioning to Chapter 4 we delve into the outcomes derived from our data. Conduct an extensive analysis of the observed trends over time. Finally, Chapter 5 concludes our research journey by summarizing our findings and suggesting areas for exploration in this crucial field.

Chapter 2

Literature Review

In the effort to combat the problem of brake shoes in Pakistan's car industry, this chapter takes a thorough look at what is already known. Fake car parts, brake shoes bring various risks to road safety, consumer health and industry reputation. To effectively deal with this issue it's crucial to review research on detecting fakes using machine learning in this area and the wider scope of counterfeit auto parts. This review not gives context to our study. Also highlights areas where current knowledge falls short that we aim to fill. By examining research from, around the world and specifically in Pakistan studying methodologies used and evaluating frameworks critically we set the groundwork for our upcoming practical work and contribute to progressing knowledge in this vital field.

2.1 Related Work

This section explores an analysis of literature focusing on the detection of fake brake shoes using machine learning. By combining findings from studies, on detection, machine learning and verifying parts we gain a comprehensive understanding of the challenges and solutions in this crucial area. The review covers the development of machine learning methods their applications in detecting products like brake shoes and their effectiveness in this context. We also examine data sources, features and techniques used in studies to differentiate between fake and authentic brake shoes. This investigation is supported by a review of the principles that guide the use of machine learning in identifying counterfeit automotive components. By synthesizing this knowledge base, we position ourselves not to grasp the state of technology but also to identify new directions and approaches for the upcoming practical phase of this research ensuring our meaningful contribution, to automotive safety and anti-counterfeiting efforts.

Xuemei Bian and colleagues carried out research, on the consumption of products specifically focusing on luxury brands. The study highlights a contradiction in consumer behavior. Although counterfeit goods are often seen as unethical, there is a growing demand for luxury items that has captured the interest of both researchers and industry experts. This review of existing literature aims to explore the reasons behind why consumers seek out luxury brands examining the psychological factors, emotional responses and coping mechanisms that shape this complex phenomenon [4].

In the realm of studies, on buying luxury brands there are common psychological findings that stand out. One key insight is the concept of the "thrill of the hunt " as discussed by Ridgway and colleagues in 2008. This idea suggests that consumers find joy and thrill in discovering and obtaining luxury items. It's akin to the excitement of a treasure hunt, where shoppers enjoy searching for hidden gems, in the world of knockoff goods [5].

Furthermore, the idea of being part of a group has been studied by scholars such, as Prendergast and Tsang (2009). This idea suggests that buyers of luxury items often feel a bond, with others who have similar buying habits. This connection adds to the allure of purchasing luxury brands for reasons [6].

Recent studies like the one conducted by Dubois and colleagues in 2019 bring a perspective to light in this field. They focus on a group of consumers who show an interest, in luxury brands due to their admiration for the skill and creativity involved in creating counterfeit products. These individuals challenge the view of item consumption.

Interestingly, the emotional responses linked to buying luxury items are diverse. While feelings of embarrassment and guilt may arise from pressures and moral conflicts (as noted by Mazar et al., 2012) there are also emotions such, as enjoyment and empowerment associated with these purchases (as highlighted by Lastovicka et al., 2011). Consumers often find pleasure, satisfaction and even a sense of empowerment through their purchases of luxury goods adding complexity to the aspects of this trend [7].

Ali and his colleagues conducted a study highlighting the concern of detecting currency in the financial sector as counterfeiters continue to adapt their tactics. They introduced DeepMoney, a system that uses Generative Adversarial Networks (GANs) to differentiate between fake banknotes. GANs, a machine learning method provide an approach through unsupervised learning, for accurate predictions. The research specifically focuses on banknotes utilizing image processing and feature recognition techniques. Through experiments with enhanced image samples they have shown the potential to achieve a 80% accuracy in identifying paper money. The availability of the code as source encourages exploration and advancement, in combating counterfeit currency [8].

Teraura, et al. introduced a system that uses a method involving two types of black ink. Regular black ink that absorbs infrared rays and special black ink that transmits them. By combining these inks the encoded information becomes susceptible, to replication by copying machines effectively identifying products. To decode the data images taken under light and infrared radiation are compared to ensure identification. Additionally encrypting the data before applying the coding technique enhances security making it harder for potential counterfeiters to replicate. Furthermore, the system has the capability to include encrypted data as numbers providing an added layer of protection, against duplication. This study offers an promising solution to address challenges related to counterfeiting [9].

P.M. Lavanya and colleagues highlighted the growing significance of technology, in addressing concerns about authenticity. Their research suggests a solution that utilizes decentralized technology to empower consumers to independently verify product authenticity. The decentralized blockchain system discussed in their study incorporates counterfeiting measures allowing manufacturers to distribute products directly without relying on traditional retail channels. This innovative approach has the potential to significantly reduce quality assurance expenses while providing consumers with a way to confirm the legitimacy of their purchases. This study reflects the increasing interest, in using technology to enhance trust and security across industries particularly in online retail [10].

Ghaith Khalil et al., conducted a study highlighting the challenges posed by product counterfeiting and theft. Surprisingly there has been exploration, into tackling these issues through the cost integration of technologies like barcodes, near field communication (NFC) and radiofrequency identification (RFID). This paper introduces a RFID based solution aimed at combating counterfeiting and theft by detecting items during purchases empowering consumers. The proposed system offers an approach for large scale retail environments utilizing low cost passive tags for efficient implementation. Furthermore the study critically evaluates a proposal by Tran and Hong uncovering vulnerabilities in their strategy. A thorough security assessment of the proposed system confirms its compliance with security standards and its resilience against security threats. This research represents an advancement, in addressing the issues of product counterfeiting and theft within contemporary retail landscapes [11].

Navid Asadizanjani et al., provides comprehensive investigation into the critical issue of counterfeit integrated circuits (ICs) infiltrating global markets. It addresses the pressing need for efficient detection and record-keeping of counterfeit ICs, an issue of increasing concern

for both businesses and governments worldwide. In response to this challenge, the study introduces a novel web application database that empowers users to share and document instances of counterfeit ICs, fostering a collective repository of knowledge.
Furthermore ,the study explores methods for detecting ICs by using image processing and machine learning to spot physical flaws in the chips. It aims to distinguish between fake ICs contributing to the enhancement of detection techniques. By combining automated detection, with data sharing this research provides stakeholders with tools and insights to effectively combat the spread of ICs [12].

Omid Aramoon and colleagues conducted an investigation, into the pressing issue of products in the integrated circuit (IC) supply chain a concern exacerbated by the global impact on the semiconductor industry. To address this challenge significant efforts have been focused on developing methods for detecting and preventing counterfeits. The study particularly emphasized the adoption of machine learning (ML) algorithms highlighting their role in shaping strategies to combat counterfeiting.

The research highlights the influence of ML algorithms on counterfeiting initiatives. It presents an overview of studies illustrating how ML has been used to either develop or thwart detection and prevention techniques for counterfeit products. Additionally the paper explores possibilities by discussing avenues for leveraging machine learning in the ongoing battle against counterfeiting. By providing this analysis the study provides stakeholders in the semiconductor industry with insights, into evolving anti counterfeit measures emphasizing the transformative impact of machine learning [13].

Ahmad and colleagues delve into the pressing issue of components, in the electronics industry a problem that affects supply chains significantly. As counterfeit parts continue to flood the market it's essential to establish methods for verifying the authenticity of circuits (ICs). Traditionally industry experts have used both nondestructive techniques to assess ICs. However these evaluations often rely on judgment leading to errors and inconsistencies.
To tackle this issue the study introduces an automated method for detecting and identifying die face delamination an defect in recycled ICs. This defect is known for being challenging to detect using methods. The researchers utilize destructive X ray computed tomography to capture 3D images of ICs. They then employ image processing techniques and machine learning algorithms to specifically target the identification of die face delamination, which includes induced cracks and damaged surfaces.

By automating the detection process and reducing involvement in decision making this research offers a solution for more accurate and efficient counterfeit detection in the electronics industry. It could significantly improve the integrity and reliability of electronic supply chains, across sectors [14].

To tackle this problem the study suggests an approach centered around using the non destructive X Ray Fluorescence Technique to analyze Tenormin® 50mg medication. This technique is preferred over chemical analysis methods due to its speed and reliability. The research involved testing ten samples of Tenormin tablets obtained from manufacturers all containing the ingredient Atenolol 50 mg along with other inactive components.

In addition to X ray analysis the study explores the use of two machine learning techniques; RBF Support Vector Machine (RBF SVM) and K Nearest Neighbor (KNN). These machine learning algorithms play a role, in automating the process of distinguishing between authentic Tenormin without relying on expert chemists.

The study results are significant demonstrating that the X Ray Fluorescence Technique can differentiate samples based on their compositions distinguishing them from others.
Moreover the method using SVM shows results, than the one based on KNN with an accuracy rate of 93% overall [15].
Akanksha Upadhyaya and colleagues delve into the pressing issue of money a threat, to both national economies and global economic growth. Counterfeiting falls within the realm of law as a crime sparking researchers to explore diverse methods for detecting and identifying fake currency. These methods range from hardware based solutions to image processing techniques and machine learning applications.
The rise of printing and scanning technologies alongside the circulation of materials has exacerbated the challenge of money. The research offers an overview of approaches put forth by researchers in detecting currency highlighting the methodologies utilized and the success rates achieved by each method.
Moreover, a comparative examination is conducted on two statistical classification methods. Logistic Regression and Linear Discriminant Analysis (LDA). For verifying currency authenticity. The findings reveal that Logistic Regression outperforms LDA with an accuracy rate of 99%.

This study provides insights for individuals seeking to implement detection techniques based on accuracy rates. It contributes to initiatives aimed at combating money and ensuring economic stability. V. Chandra Shekhar Rao and colleagues delved into machine learning methods used to spot news focusing on how deep learning is implemented. The study tackles the limitations and hurdles linked to these strategies.

The projects main approach involves developing a model by employing a Logistic Regression classifier, for detecting news, which has proven effective in sorting tasks. By utilizing TF IDF (Term Frequency Inverse Document Frequency) features the project constructs a model for identifying news with the goal of improving accuracy.

This projects key aim is to spot information using Natural Language Processing (NLP) and machine learning, mainly analyzing the content of news articles. Once the machine learning model for detecting fake or true news is created it gets rolled out via a web interface using Python Flask.

This study adds to the fight, against the spread of news by utilizing machine learning and NLP with an implementation strategy geared towards boosting the accuracy and effectiveness of spotting fake news [17].

The rise of printing and scanning technologies alongside the circulation of materials has exacerbated the challenge of money. The research offers an overview of approaches put forth by researchers in detecting currency highlighting the methodologies utilized and the success rates achieved by each method.

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This study provides insights for individuals seeking to implement detection techniques based on accuracy rates. It contributes to initiatives aimed at combating money and ensuring economic stability.

Kiarash Ahi and colleagues have introduced techniques, for spotting electronic parts that are also useful in quality assurance procedures. Their research utilizes terahertz pulsed laser systems to delve into the material properties allowing for the differentiation between components and their counterfeit duplicates. Moreover these methods assist in pinpointing material flaws within the components.

The study involves examining indices and absorption coefficients in counterfeit parts compared to their authentic counterparts. By analyzing Fourier Transform of transmitted terahertz pulses unusual materials present in components can be identified. Furthermore, by studying the reflected terahertz pulse one can ascertain the thicknesses of layers in the components thus revealing layers.

The research further uncovers recycled, sanded and blacktopped parts through these investigations. Particularly interesting is how visualizing terahertz raster scanning data as images aids in identifying ICs with dislocations. Similarly by using raster scanning of reflected pulses to create images of component surfaces one can explore materials and sanded regions. This method helps unveil recycled components [18].

Tao Zhang and colleagues conducted a research project focusing on tackling the challenge of identifying surface defects, on brake pads using machine learning techniques. They developed an automated defect detection system that leverages learning to address this issue. The study kicked off by creating an image acquisition system and compiling a dataset of brake pad images. They then introduced a detection method utilizing Convolutional Neural Networks (CNN). The dataset was employed to train the CNN model for detecting and categorizing defects.

In addition, the study proposed another defect detection approach based on Full Convolution Networks (FCN) to further enhance system performance. Both methods underwent testing demonstrating their effectiveness in identifying brake pad defects and accurately categorizing them. The CNN based method showed efficiency in defect detection while the FCN based strategy achieved accuracy in recognition and overall performance levels. This research contributes to advancing automated defect detection systems for brake pads providing insights for industries, on this crucial automotive component [19].

Pan and colleagues introduced a learning method to detect products by focusing on detailed characteristics. Their innovative approach, integrated into industrial technology systems provides a system, for efficiently spotting counterfeit goods. By utilizing deep learning technology their strategy marks a progression in the field.

Díaz and Padilla devised networks to identify counterfeit items in fast paced assembly lines aiming to streamline the detection process. Their method, featured in IFAC PapersOnLine presents a solution for identifying fake products in automated manufacturing settings. Through the application of deep learning methods their technique signifies a leap, in counterfeit detection efforts promising enhanced security measures and improved detection capabilities [21].

Verma, Maheshwari and Jain introduced a deep learning method to identify goods in online shopping presenting a strong strategy to tackle the issue of counterfeit products, on the internet. Their technique, outlined in a research paper published in the International Journal of Intelligent Systems and Applications in Engineering utilizes deep learning methodologies to improve the precision and effectiveness of spotting items. By tackling the obstacles encountered on e commerce sites their strategy provides increased security, for both consumers and businesses engaged in trade [22].

Rajput, Verma and Yadav delved into the realm of spotting products through the utilization of machine learning methods shedding light on ways to improve the precision of detection procedures. Their study, presented at the International Conference, on Advanced Computing & Communication Systems plays a role in pushing forward the domain of detection by making use of machine learning algorithms. Through the exploration of approaches their research offers resources and strategies, for tackling counterfeit items [23].

Lu and colleagues introduced a method at the Chinese Control And Decision Conference aimed at identifying products through deep learning. Their technique aims to improve the precision and speed of spotting goods leading to security measures and heightened detection capabilities, across different industries. Through the use of learning strategies their method provides a tool in the fight against fake products paving the path for increased security and protection, for consumers [24].

2.2 Research Gap

The research gap concerning the "Classification of Counterfeit Brake Shoes using Machine Learning" is mainly due to the lack of emphasis on applying machine learning techniques to address the issue of brake shoes. While previous studies have covered products in areas, such as automotive components, the specific focus on detecting fake brake shoes through machine learning methods seems to be an overlooked area.

Moreover, existing research tends to have a scope often discussing counterfeit products rather than delving deep into the intricacies and specifics of counterfeit brake shoes. The importance of brake shoes as a safety component in automobiles calls for attention and research.

Furthermore, there is a need for investigation into the effectiveness and precision of machine learning models, especially deep learning approaches in distinguishing between counterfeit brake shoes. Developing robust and efficient machine learning algorithms tailored specifically for detecting brake shoes presents an avenue for further exploration.

Additionally the lack of datasets containing samples of counterfeit and authentic brake shoes poses a challenge in developing and validating machine learning models in this context. Establishing a representative dataset for detecting brake shoes is vital to effectively address this research gap. In short the research gap, in "Identification of Fake Brake Shoes using Machine Learning" centers on the necessity for studies addressing the hurdles posed by counterfeit brake shoes creating accurate machine learning models and having relevant datasets for training and assessment. Bridging this divide will significantly enhance safety. Reduce the dangers associated with fake brake shoes.

The study delved into the intricacies of the automotive supply chain and regulatory measures taken to tackle auto parts shedding light on the complex network within which these fake components operate. Additionally it emphasized the role of machine learning, deep learning techniques in strengthening efforts to detect counterfeits.

As the study advanced ,it became clear that using machine learning to differentiate brake shoes from ones is an area ripe for exploration. This research has highlighted the necessity for datasets and algorithms specifically designed for brake shoes paving the way for further exploration in this field.

Essentially this study lays a foundation for endeavors aimed at improving safety and security by leveraging machine learning to combat the widespread threat of counterfeit brake shoes. By tackling this concern we play a role in protecting not the economy but also the well being of numerous people who depend on their vehicles parts to function properly.

Chapter 3

Methodology

3.1 Workflow

The workflow of our project starting from data collection to the end of model evaluation has been represented in Fig 3.1.

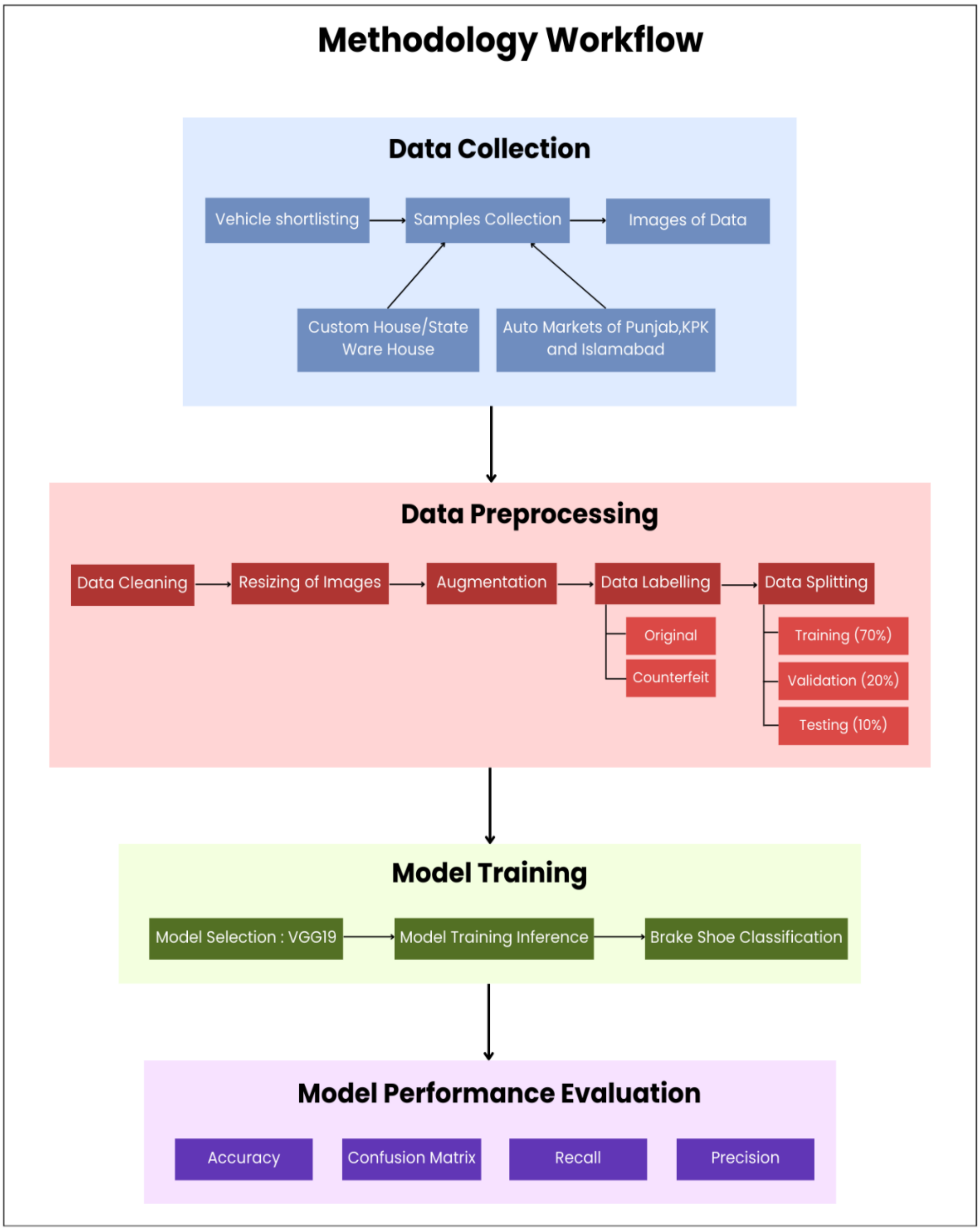


Figure 3.1. Flow chart for described Methodology

3.2 Data Collection

The primary task, in selecting brake shoes involved narrowing down the vehicles for both computational evaluations. Various factors and trade offs were taken into account when deciding on the vehicle, including car models, market availability, specific car makes vehicles prone to accidents, input from trusted car mechanics and more. Following an assessment of these considerations the Toyota Corolla AE86 was chosen for data gathering due to its usage and the ease of acquiring its brake shoes.

After selecting the vehicle the next step involved procuring samples of brake shoes from sources. The Gallery of Custom House Islamabad served as a location for accessing samples of both genuine products confiscated by officials. Additionally data collection took place at the State Warehouse (SWH) of Pakistan Customs. As there were samples at the Custom House visits were made to auto part markets in Lahore, Rawalpindi, Faisalabad and Islamabad for sample collection.

The final stage included capturing images of the samples from angles—resulting in, over two thousand images taken from perspectives. Through these steps the process of data collection was successfully concluded.

In the sections we will delve into the preparation of data.

3.3 Data Preprocessing

Before you start training with the data there are tasks involved in prepping the data. These tasks include getting rid of samples adjusting image sizes annotating data sorting data into two groups and dividing the data into categories. Lets go through each of these steps, in detail.

3.3.1 Data Cleaning:

The initial step in data preprocessing involves data cleansing. Since the dataset was compiled manually, it contained unclear images, which were eliminated to enhance data quality. A comprehensive review of all data was conducted to guarantee consistency and precision, in the outcomes.

3.3.2 Resizing of Images:

Resizing involves adjusting the size of an image either making it smaller or larger based on the requirement. It also standardizes the data from images of varying resolutions, to a scale. The dataset contained images of sizes and qualities. It was essential to resize them to a consistent dimension.

Consequently, resizing was performed with dimensions of 512x512 and color conversion applied.

3.3.3 Data Labelling:

The research is related to the classification of counterfeit and original brake shoes, the dataset was labelled as counterfeit and original brake shoes. The percentage of original and counterfeit samples was 40 per cent and 60 per cent, respectively.

3.4 Model Training

Models which are selected for brake shoe classification are VGG19, Convolutional Neural Network, and Multi-layer perceptron. These models are described below:

3.4.1 VGG19

VGG-19 is an image classification and object identification deep convolutional neural network (CNN) architecture. The "19" in VGG-19 pertains to its 19 layers, which include 16 convolutional layers and 3 fully connected layers. The architecture was first described in the publication "Very Deep Convolutional Networks for Large-Scale Image Recognition" by Karen Simonyan and Andrew Zisserman, and it quickly gained popularity due to its simplicity and efficacy. Being a deep convolutional neural network (CNN) architecture designed for image classification and recognition, VGG-19 finds applications in various areas of daily life. VGG-19 is primarily designed for image classification tasks [25]. This can be applied in systems that require object detection and classification in images, such as photo organization apps, content-based image retrieval systems, and image recognition in social media.

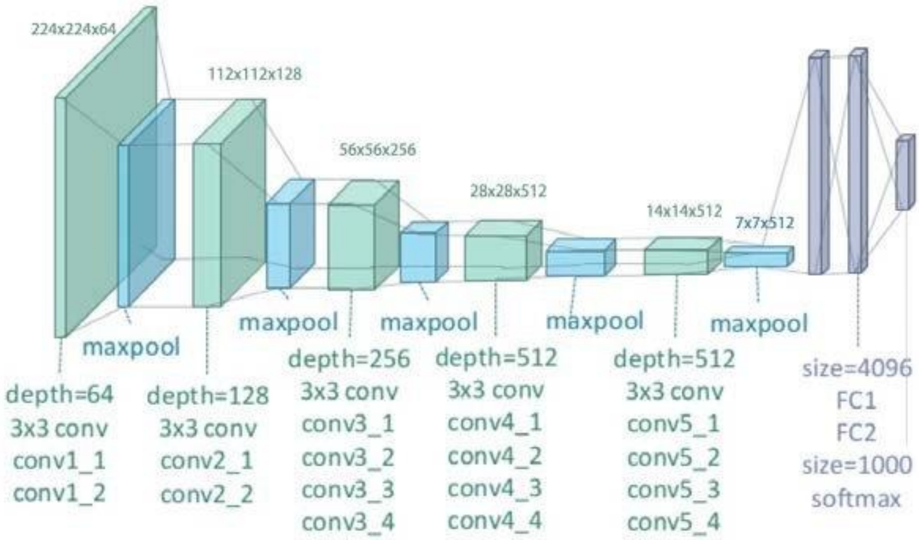


Figure 3.2. https://www.researchgate.net/figure/llustration-of-the-network-architecture-of-VGG-19-model-conv-means-convolution-FC-means_fig2_325137356

3.4.2 Convolutional Neural Network:

. Convolutional neural networks serve as the components of deep learning algorithms. They consist of three layers; the layer, pooling layer and Fully Connected Dense layer[26]. The Convolutional layer, positioned at the forefront of CNNs carries out operations, on input data using parameters like input data, filters and feature maps. The pooling layer, also referred to as a down sampling layer reduces data dimensions through processes such, as max pooling and average pooling to simplify the complexity of the information. Finally, the Connected layer resides at the tail end of the model architecture and links preceding layers to the output layer where classification outcomes are determined as either 0 or 1

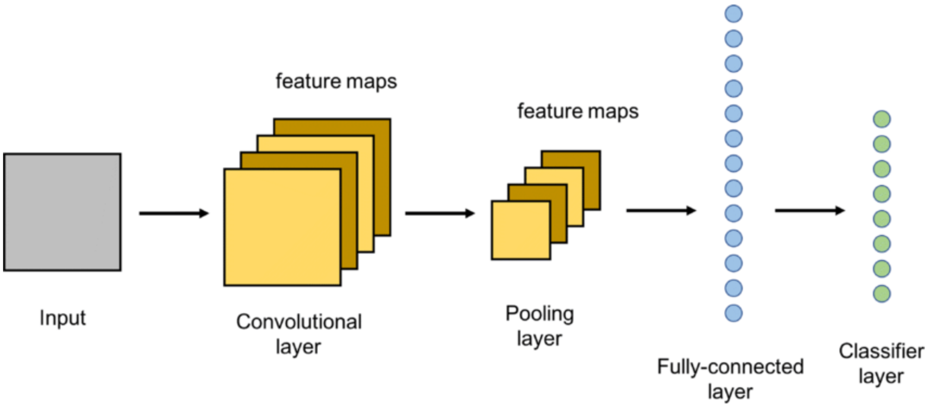


Figure 3.3. https://www.researchgate.net/figure/A-simple-convolutional-neural-network-CNN-and-its-main-layers_fig1_339008531

3.4.3 Multi-Layer Perceptron:

The Multi Layer perceptron is a type of network that operates with a feedforward mechanism. It consists of three layers; the input layer, hidden layer and output layer. The input layer serves as the entry point, for data into the model through neurons that represent the dimensions of the input data. Positioned between the input and output layers the hidden layers play a role in processing information. Can vary in number based on the complexity of the model. Most of the work takes place within these layers. Meanwhile the output layer is responsible for generating model outputs corresponding to input classes[27]. For example, it may have one neuron for classification or multiple neurons, for handling classes

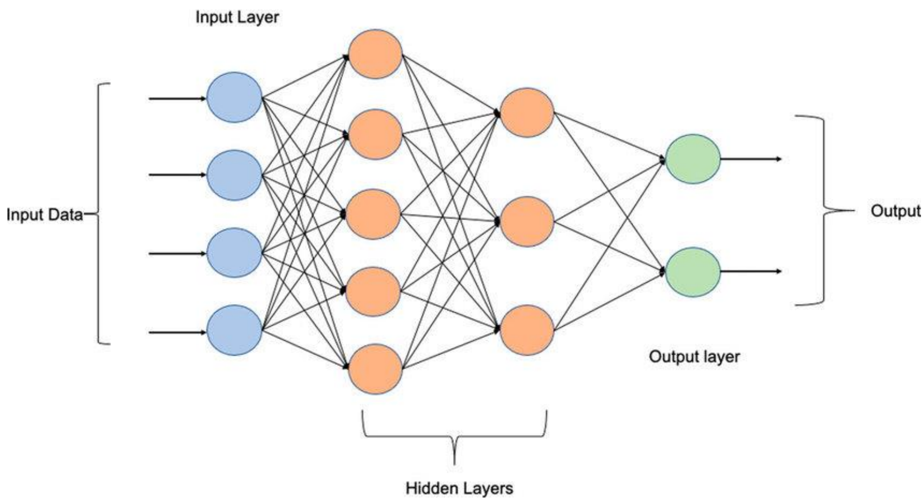


Figure 3.4. https://www.researchgate.net/figure/Multi-layer-perceptron-MLP-NN-basic-Architecture_fig2_354817375

3.5 Brake Shoe Classification

The pre-trained model selects a random image and then classifies whether the brake shoe is original or counterfeit; the labelling of the model is then compared with the actual file to determine whether the classification of the brake shoe was true or false and whether it counts to the accuracy of results.

3.6 Performance Evaluation

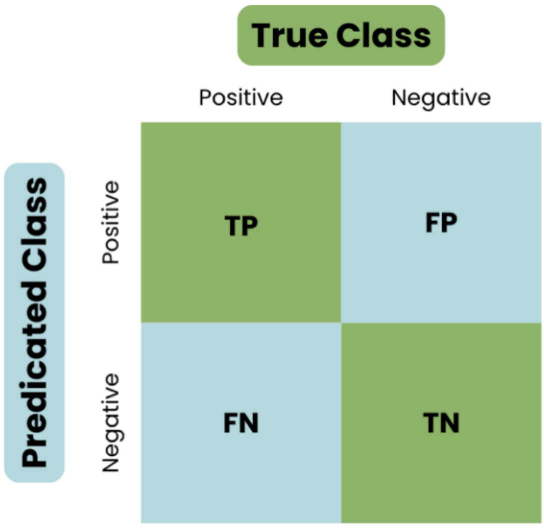
There are several evaluation parameters which are measured after model training to check efficiency of model. Some of them are discussed below:

3.6.1 Confusion matrix

A confusion matrix is a tool used in machine learning to evaluate the performance of a classification model. It shows the accuracy of the model by displaying positives true negatives, false positives and false negatives. This chart helps in assessing how well the model performs, identifying errors, in classification and enhancing prediction accuracy. [28].

In a nutshell a confusion matrix is an N*N grid used to measure how effective a classification model is for N target classes. It compares the target values with the predictions made by the machine learning model giving us insights into its performance and error patterns.

For classification scenarios we typically use a 2 x 2 matrix with four values as illustrated below



Let’s break down the components of this matrix;

- The target variable has two outcomes; Positive or Negative.
- The columns depict the values of the target variable.
- The rows show the predicted values of the target variable

Confusion Matrix has following important terms:

1. **True Positive (TP):**

When the predicted value matches the value. When both predicted and actual classes align. The real value turned out to be positive. The model correctly forecasted an outcome.

2. **True Negative (TN):**

When the predicted value matches the value or when the predicted category aligns, with the category. The true value was negative. The model correctly anticipated a result.

3. **False Positive (FP):** A situation where there was a prediction and the result was negative. The model wrongly projected an outcome. This is commonly referred to as type I error.

4. **False Negative (FN):**

An instance where there was a prediction made. The actual value was positive. The model erroneously foresaw a result. This is also known as type II error.

3.6.2 Precision

Precision is a measure in machine learning that assesses how accurate the positive predictions made by a classification model are. It becomes crucial in cases where the consequences of positives (wrongly predicting a result) are significant. Precision is calculated as the proportion of predictions, to the total number of instances predicted as positive by the model [29]. Precision, referred to as Positive Predictive Value gauges the precision of positive forecasts generated by a model and is expressed through the formula provided.

$$Precision = \frac{TP}{TP + FP} \qquad (2.1)$$

3.6.3 Recall

In the realm of machine learning Recall—also referred to as Sensitivity or True Positive Rate—is a metric that evaluates a classification models effectiveness, in detecting all instances of a particular class within a dataset. The calculation of recall hinges on the proportion of positives against the sum of true positives and false negatives [29]. This metric offers insights into the models proficiency in recognizing occurrences of the positive class. Here is the formula for reference

$$Recall = \frac{TP}{TP + FN} \qquad (2.2)$$

3.6.4 Accuracy

In the field of machine learning, accuracy serves as a metric for tasks like image classification. It measures the proportion of predicted outcomes compared to the instances to assess the overall performance of a model. When it comes to image classification specifically accuracy indicates the percentage of images correctly identified by the model [30].

The formula for accuracy is as follows:

$$Accuracy = \frac{1}{n}\sum_{i=1}^{n}\frac{TPi + TNi}{TPi + FNi + FPi + TNi} \qquad (2.3)$$

Chapter 4

Results and Discussion

4.1 Dataset Description

The study utilized a dataset containing pictures of brake shoes gathered from cities such as Islamabad, Lahore, Faisalabad, Rawalpindi and Multan. There were a total of 2000 images in the dataset with 800 being authentic and 1200 being counterfeit images. Each image was carefully labeled as either genuine or fake serving as the foundation for training and assessing machine learning models. Here are some samples, from the dataset collection;

:

Figure 4.1. Images of counterfeit and original brake shoe from dataset collected

4.2 Location-wise Data Collection

Data was gathered from cities to make sure the dataset was diverse and representative. Pictures were taken from markets of various cities showcasing a variety of brake shoes available locally. These images varied in size

4.3 Machine Learning Models for Classification

Three machine learning models were employed for classification of original and counterfeit brake shoes:

4.3.1 CNN Model

The classification of brake using a CNN model involves a structure, with 5 layers beginning with 3 layers followed by 2D layers and max pooling layers. To bridge the layer and the final dense layer a flatten layer is employed. The dense layer serves as the component of the model. Is responsible, for categorizing data based on probabilities.

Model: "cnn_model"

Layer (type)	Output Shape	Param #
input (InputLayer)	[(None, 512, 512, 3)]	0
conv2d (Conv2D)	(None, 510, 510, 32)	896
max_pooling2d (MaxPooling2D)	(None, 255, 255, 32)	0
conv2d_1 (Conv2D)	(None, 253, 253, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 126, 126, 64)	0
conv2d_2 (Conv2D)	(None, 124, 124, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 62, 62, 128)	0
flatten (Flatten)	(None, 492032)	0
dense (Dense)	(None, 128)	62980224
outputs (Dense)	(None, 1)	128

Total params: 63073600 (240.61 MB)
Trainable params: 63073600 (240.61 MB)
Non-trainable params: 0 (0.00 Byte)

Figure 4.2. CNN Architecture used for model training

4.3.2 MLP Model

MLP model comprised of one input layer. Hidden layer and dense layer is used for training on brake shoe dataset. It consists of 3 dense layers to match the output dimensions with input dimensions and produced output on the basis of input data.

Layer (type)	Output Shape	Param #
mlp_input (InputLayer)	[(None, 512, 512, 3)]	0
flatten (Flatten)	(None, 786432)	0
dense (Dense)	(None, 512)	402653696
dense_1 (Dense)	(None, 256)	131328
dense_2 (Dense)	(None, 128)	32896
dense_3 (Dense)	(None, 64)	8256
mlp_outputs (Dense)	(None, 1)	64

Figure 4.3. MLP Architecture used for Model training

4.3.3 VGG 19 Model

VGG 19 model architecture used for training is obtained from Keras library. This model is pre-trained on ImageNet dataset. The top layers are used as trainable to train on given data using technique of transfer learning. This model comprised of all 16 convolutional and 3 fully connected layers at the end for training.

```
Model: "model1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input (InputLayer)          [(None, 512, 512, 3)]     0

 tf.__operators__.getitem (  (None, 512, 512, 3)       0
 SlicingOpLambda)

 tf.nn.bias_add (TFOpLambda  (None, 512, 512, 3)       0
 )

 block1_conv1 (Conv2D)       (None, 512, 512, 64)      1792

 block1_conv2 (Conv2D)       (None, 512, 512, 64)      36928

 block1_pool (MaxPooling2D)  (None, 256, 256, 64)      0

 block2_conv1 (Conv2D)       (None, 256, 256, 128)     73856

 block2_conv2 (Conv2D)       (None, 256, 256, 128)     147584

 block2_pool (MaxPooling2D)  (None, 128, 128, 128)     0

 block3_conv1 (Conv2D)       (None, 128, 128, 256)     295168

 block3_conv2 (Conv2D)       (None, 128, 128, 256)     590080

 block3_conv3 (Conv2D)       (None, 128, 128, 256)     590080

 block3_conv4 (Conv2D)       (None, 128, 128, 256)     590080

 block3_pool (MaxPooling2D)  (None, 64, 64, 256)       0

 block4_conv1 (Conv2D)       (None, 64, 64, 512)       1180160

 block4_conv2 (Conv2D)       (None, 64, 64, 512)       2359808

 block4_conv3 (Conv2D)       (None, 64, 64, 512)       2359808

 block4_conv4 (Conv2D)       (None, 64, 64, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 32, 32, 512)       0

 block5_conv1 (Conv2D)       (None, 32, 32, 512)       2359808

 block5_conv2 (Conv2D)       (None, 32, 32, 512)       2359808

 block5_conv3 (Conv2D)       (None, 32, 32, 512)       2359808

 block5_conv4 (Conv2D)       (None, 32, 32, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 16, 16, 512)       0

 global_average_pool (Globa  (None, 512)               0
 lAveragePooling2D)

 outputs (Dense)             (None, 1)                 512

=================================================================
Total params: 20024896 (76.39 MB)
Trainable params: 20024896 (76.39 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure 4.4. VGG199 Architecture for Model Training

4.4 Model Training

After selecting the models for classification, those are models are being trained on dataset with 80/20 splits. Other parameters selected for training phase has been presented in Table 4.1.

Model	Test/Train split	Epochs	Batch size	Learning Rate
CNN	80/20	15	16	0.0001
MLP	80/20	15	16	0.0001
VGG19	80/20	15	16	0.0001

4.5 Results obtained from Trained Models

After training machine learning models on provided dataset for 15 epochs and 16 batch size with learning rate of 0.0001, following performance measures has been obtained with training and testing accuracy and loss presented from Figure 4.5 to 4.7. Following results are obtained by different models:

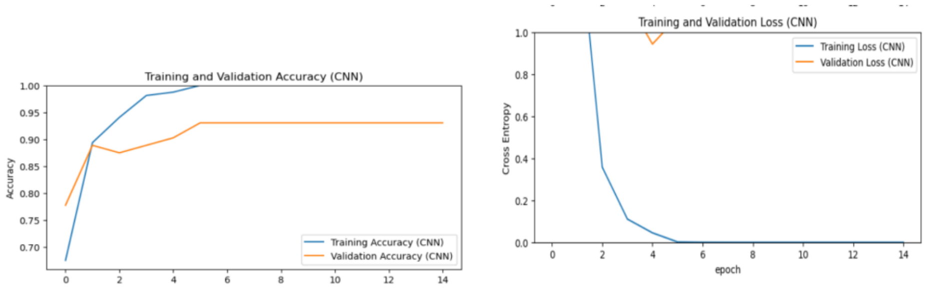


Figure 4.5. Training and Validation Accuracy and loss of CNN Model

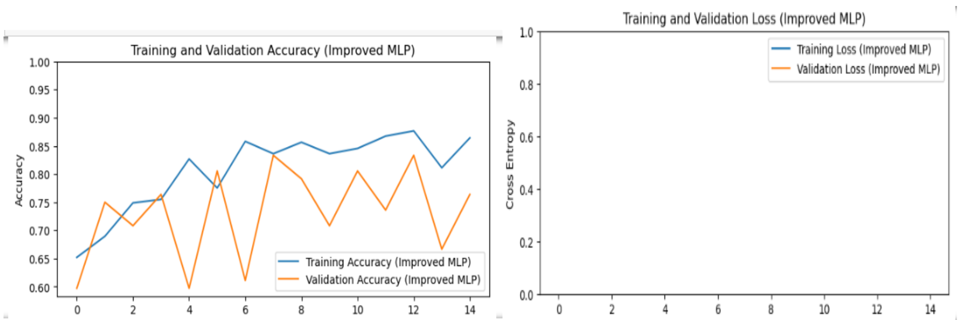


Figure 4.6. Training and Validation Accuracy and Loss of MLP Model

Figure 4.7. Training and Validation Accuracy and Loss of VGG19 Model

4.6 Prediction on Test Data

After model training, the model is being tested on test data. During testing phase, data with true labels is given to model to check how well it performed on the given data. For that purpose, confusion matrix is used containing real number of true positive and true negatives. Following confusion matrices are obtained from all the three models from Fig 4.8 to 4.10.

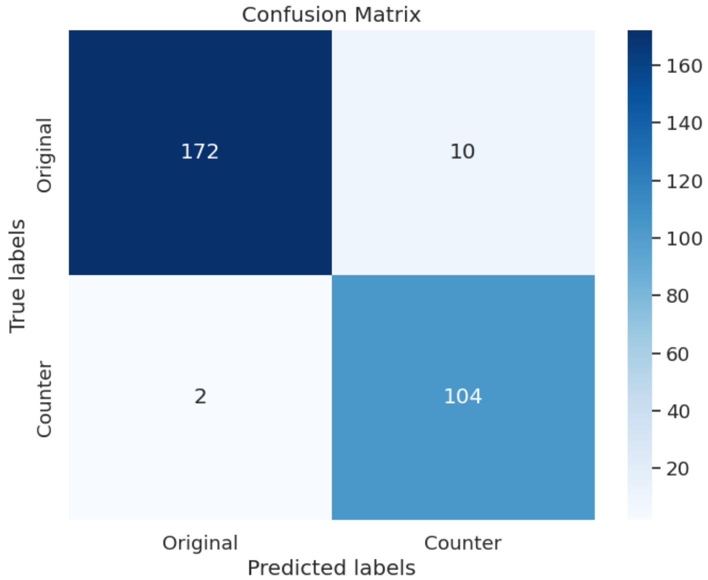


Figure 4.8. Confusion Matrix for CNN Model

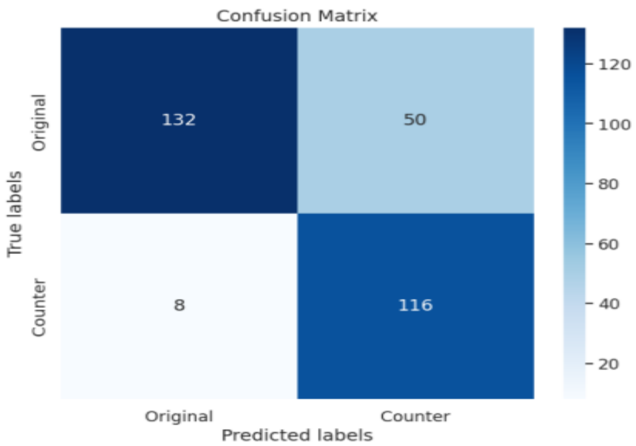


Figure 4.9. Confusion Matrix for MLP Model

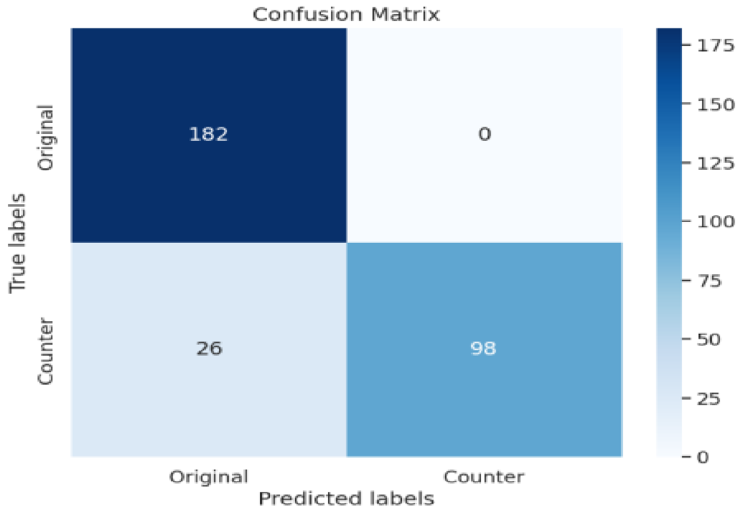


Figure 4.10. Confusion Matrix for VGG19 Model

4.7 Comparative Analysis

The study compared the performance of models used in the research. Three models. VGG19, Convolutional Neural Network and Multi Layer Perceptron were utilized. Performance was assessed using measures, like accuracy, precision, recall and F1 score. These metrics are commonly employed to gauge model effectiveness. The results from all three models are presented in a table showing that VGG19 had the accuracy compared to the models with its other values surpassing those of the remaining two models. This indicates that VGG19 yielded the results, for distinguishing between authentic and counterfeit brake shoes in our study

Model	Accuracy	Precision	Recall	F1-score
CNN	0.90	0.90	0.90	0.90
MLP	0.81	0.84	0.81	0.81
VGG19	0.92	0.93	0.92	0.91

4.8 Predicted Images

After finishing the training and testing phases the model was provided with images of a brake shoe, for prediction. The model accurately predicted the output image to match the given label with a few errors. Several examples of predicted outputs, from models are showcased in Figure 4.11.

Figure 4.11. Predicted outcomes of different models with true labels

Chapter 5

Conclusion and Future Aspect

In summary, this research illustrates how Machine Learning models effectively differentiate between original and fake brake shoes. By using Convolutional Neural Network (CNN), Multilayer Perceptron (MLP) and VGG 19 models, we have successfully addressed the issue of detecting products in the footwear industry. Our detailed examination of each model's performance, backed by confusion matrices and accuracy measures offers insights into their strengths and limitations.

The comparison shows that the VGG 19 model stands out as a solution for differentiating two classes of brake shoes. Its high accuracy and reliability highlight its potential as a tool in combating anti-counterfeiting activities. By utilizing the deep learning capabilities of the VGG 19 architecture, we make progress in counterfeit detection methods contributing to the ongoing battle against unlawful trade practices.

Moreover, tuning techniques enhance the model's performance and dependability. By adjusting hyperparameters and optimizing feature engineering processes, we improve the models ability to accurately detect items. These results not only confirms the effectiveness of machine learning in detection but also emphasize the importance of continuous research and innovation to develop more sophisticated anti counterfeiting strategies.

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